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What can price volatility tell us about market efficiency? Conditional heteroscedasticity in historical commodity price series

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Abstract The development in the working of markets has been an important topic in economic history for decades. The volatility of market prices is often used as an indicator of market efficiency in the broadest sense. Yet, the way in which volatility is estimated often makes it difficult to compare price volatility across regions or over time for two reasons. First, if prices are non-stationary, the variance is inflated. Second, the variance of commodity prices contains information on a number of region- and time-specific factors that are not related to market efficiency. Hence, the popular coefficient of variation and related indicators are not adequate measures of the efficiency of markets and are incomparable across regions. As a solution, we suggest using a conditional heteroscedasticity model to estimate the residual (conditional) variance of commodity prices. This measure reflects how markets react to unexpected events and can therefore be seen as a measure of market efficiency. Using this approach on grain prices from the Early Modern Pisa, Paris, Vienna, and Japan, we find that the residual price volatility had declined (and market efficiency increased) in the European markets in the late sixteenth century while it remained stable in Japan.

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1 Introduction

Researchers have always been aware of classifying the working of markets. Ancient or Early Modern markets were often classified as "conspicuously conventional, irrational and status-ridden" when an author wanted to stress the economic backwardness of a society, or when the opposite point of view was defended, as "a sphere of activity with its own profit-maximizing, want-satisfying logic and rationality" Andreau (2002, 15).

Since quantitative ways to measure market efficiency are in short supply, this discussion has been allowed to survive until relatively recent times. From an economic–theoretical perspective (i.e., Temin 2002), studies have shown that even in ancient times markets exhibited a remarkable degree of efficiency, a fact that is also widely acknowledged among scholars of medieval economies (i.e., Britnell and Campbell 1995). This view, however, is in contrast with the evidence from those studies that make use of price volatility of (largely) agricultural products. The demand for such products is generally price inelastic; hence, supply shocks might be the primary source of price fluctuations. Since market integration leads to arbitrage between different markets thereby reducing price differences, a decrease in price volatility is thought to be indicative of well-functioning markets (i.e., Persson 1999). These studies often find an increase in market efficiency from the late medieval period onward.

Indeed, this is exactly what we find if we look at Table 1. With the exception of the sixteenth century, there is a clear downward trend in the coefficient of variation from 385 BC until 1900. Hence, according to this measure, the further back in time one goes, the less efficient are the markets.

How can the evidence based on historical analyses, which indicates an already relatively efficient market in the medieval period, be squared with strong changes in price volatility over time? It has been widely acknowledged that the volatility of prices is affected by more factors than purely the market mechanism (i.e., Persson 1999, pp 107–108). A notable example can be found in Table 1 in the estimates for the sixteenth century. Here, we can see that price volatility in the sixteenth century, during what is referred to as "the price revolution" (Munro 2003), seems extraordinarily high. In fact, according to the above table, price volatility [measured by coefficient of variation (CV)] in England between 1500 and 1650 AD was as high as it was in Babylonia between 250 and 150 BC. Yet, very few people would argue that market efficiency actually declined during that period.[1]

[1] An exception is Bateman (2007) who argues that market efficiency follows a U-shaped pattern with a trough during the sixteenth century.

Table 1 Coefficient of variation (CV) of barley per period and country

Country	Period	Product	Mean	Std deviation	CV	Unit	Source
Babylon	385–250 BC	Barley	19.807	19.032	0.961	shekel/100 l	Slotsky (1997), Vargyas (2001)
Babylon	250–150 BC	Barley	10.900	7.088	0.650	shekel/100 l	Slotsky (1997), Vargyas (2001)
Babylon	150–61 BC	Barley	21.263	17.518	0.824	shekel/100 l	Slotsky (1997), Vargyas (2001)
England	1209–1347 AD	Barley	0.408	0.154	0.378	shilling/bu	Clark (2004)
England	1350–1500 AD	Barley	0.423	0.147	0.347	shilling/bu	Clark (2004)
England	**1500–1650 AD**	**Barley**	**1.264**	**0.800**	**0.633**	**shilling/bu**	Clark (2004)
England	1650–1800 AD	Barley	2.393	0.696	0.291	shilling/bu	Clark (2004)
England	1800–1900 AD	Barley	4.300	1.069	0.249	shilling/bu	Clark (2004)
Florence	1325–1347 AD	Barley	10.183	3.278	0.322	denier/setier	de La Roncière (1982)
Modena	**1554–1650 AD**	**Barley**	**98.753**	**49.927**	**0.506**	**soldi/staro**	Basini (1974)
Modena	1650–1700 AD	Barley	120.000	31.503	0.263	soldi/staro	Basini (1974)
Vienna	**1500–1650 AD**	**Barley**	**28.834**	**24.558**	**0.852**	**kreuzen/metzen**	Pribram (1938)
Vienna	1650–1800 AD	Barley	61.299	28.419	0.464	kreuzen/metzen	Pribram (1938)

Bold values denote estimates for the period of 'Early Modern price revolution'

There are also several other factors that, although they do play a role in broadly defined market efficiency, are profoundly country (or time) specific. Agricultural structure, for one, may have a strong influence on seasonality and inter-annual volatility. A clear example can be found in China where the Anhui province has a single rice harvest per year, while Guangxi and Guangdong have two and Hainan even has three. Consequently, even if one harvest failed, when the second (or third) harvests become available at the end of the year, prices would still be lowered. This is completely different from Java, for example, which has a single yearly rice harvest, a yield that made up roughly 50% of total value added in agriculture during the twentieth century (Van der Eng 1996, Table A.1.2). It is important to note that although multiple harvests clearly reduce price fluctuations, being dependent on the climate of a country, it does not say much about the efficiency of the market. As such, simply interpreting the CV of prices in such different regions as indication of market efficiency differences would be misleading.

This paper argues that within a geographical region, standard volatility measures tell us little about the actual development of market efficiency over time and are not comparable across countries having different product structures, consumer preferences, and weather conditions.[2] Hence, we critically examine the existing measure of volatility to find the one that not only is comparable across regions (or, at least contains less incomparable factors) but can also be used to proxy market efficiency.

[2] Alternatively, we could say that standard volatility measure tells us a lot about market integration but does so in such a noisy and incomparable way that we cannot rely on them.

Building on many related studies (i.e., Persson 1999; Söderberg 2004), we argue that the standard deviation of the log of the detrended price series and that of regression residuals from some structural models of prices (or, in the absence of necessary data, an ARMA model) can both be used, although the latter is preferable. It is important to note that this paper focuses on the measurement of volatility within a single region over time (a time series perspective) and not on measuring the spatial variability of prices (a cross-sectional perspective). In the next section, we briefly explain the problem with traditional measures and argue that both the trend and volatility of these measures are problematic. This is elaborated upon in Sects. 3 and 4 where we discuss the effects of the trend and the volatility, respectively. Section 5 discusses an alternative measure of dispersion that is comparable over time, as well as across countries. Section 6 applies these theories to empirical models. Section 7 concludes the paper.

2 Problems with the standard measure of volatility

The coefficient of variation (CV) is often used as a measure of market efficiency (Persson 1999). The problem, however, is that, as a measure of price volatility, the CV captures many external and internal market factors ranging from agricultural structure and consumption to the effects of plagues, trade, and monetary shocks. The result is that this measure captures factors that, while they may differ among countries, do not directly influence market efficiency. In the next sections, we will look at the traditional measures and show that statistics reflecting the spread of a variable around its arithmetical average (unconditional mean) contain a number of region/culture-specific factors unrelated to the defined efficiency. As such, traditional measures based on the unconditional mean, such as the CV or the standard deviation of log prices (being comparable to the CV),[3] are not comparable over time and space. Instead, we suggest using a conditional heteroscedasticity methodology to draw conclusions on the market integration of different societies in different periods and compare them from this perspective. This methodology allows us to see if markets managed to react quicker to unexpected price shocks.

As a first step, it is important to precisely define what is meant by efficiently working markets. We adopt a very general definition of risk in commodity markets. By risk we mean the degree of uncertainty regarding future prices. This is often approximated by the degree of volatility of price series, which is deducible from the expectation that if risk management techniques are efficient, they will reduce uncertainty resulting in smoother prices. Generally speaking, one may expect such

[3] That the two measures of dispersion are almost equivalent can be shown easily. Let d be equal the deviation from the mean: $d_t = y_t - \bar{y}$. Now, the Coefficient of Variation can be expressed as follows: $CV = \sqrt{\frac{\sum_{t=1}^{T}(y_t-\bar{y})^2}{n}}\frac{1}{\bar{y}} = \frac{\sqrt{\sum_{t=1}^{T} d_t^2}}{\sqrt{n}\bar{y}}$ while the standard deviation of the log series is the following: $\sigma_{\ln y} = \sqrt{\frac{\sum_{t=1}^{T}\left(\ln y_t - \overline{\ln y}\right)^2}{n}} = \frac{\sqrt{\sum_{t=1}^{T}\ln\left(\frac{y_t}{\bar{y}}\right)^2}}{\sqrt{n}} = \frac{\sqrt{\sum_{t=1}^{T}\ln\left(1+\frac{d_t}{\bar{y}}\right)^2}}{\sqrt{n}} \approx \frac{\sqrt{\sum_{t=1}^{T}\left(\frac{d_t}{\bar{y}}\right)^2}}{\sqrt{n}} = \frac{\sqrt{\frac{1}{\bar{y}^2}\sum_{t=1}^{T} d_t^2}}{\sqrt{n}} = \frac{\sqrt{\sum_{t=1}^{T} d_t^2}}{\sqrt{n}\bar{y}}$. In the last derivation, we made use of the approximation that for small values of x, $\ln(1+x) \approx x$.

reduction in price volatility to arise from four major types of risk management techniques.

1. Intertemporal risk reduction (storage, for example) can reduce seasonal or even cyclical movement of prices. This oldest form of risk management in the markets of basic foodstuffs possibly saw the earliest large-scale involvement of the state in the Ancient East. This practice continued during the medieval and early modern periods, although its importance has been questioned (Fenoaltea 1976; McCloskey and Nash 1984; Komlos and Landes 1991; Will et al. 1991; Poynder 1999).
2. Spatial market integration (or spatial diversification) reduces volatility through linking different coexisting markets by means of trade. Obviously, if different regions trade with each other, price equalization may reduce the price effect of idiosyncratic shocks. Furthermore, improving international relations (trade liberalization, longer periods of peace) facilitates the technological development of transportation (for example, large cargo vessels, refrigeration). This type of market integration has been subject of several studies (i.e., Jacks 2005; Ó Gráda 1992; Keller and Shiue 2007; Özmucur and Pamuk 2007; Federico and Persson 2007; Studer 2008).
3. Increased diversification of the consumption structure is another way in which to stabilize fluctuating prices. If consumers have a wide range of substitutes from which to choose, prices will not be impacted as greatly by product-specific shocks. We can find several historical examples for diversifying consumption through discoveries and long-distance trade, such as the introduction of maize, rice, and potato in Europe, as well as through technological developments (margarine as a substitute for butter) (Ó Gráda 1992; Reis 2005).
4. Finally, innovations through product development may also contribute to less volatility and more stable yields. Even though this could be associated with genetic engineering, selective breeding can be seen as an early version of product development (i.e., Overton 1996, pp 113–114).

Altogether, the techniques mentioned above contributed to the reduction in uncertainty of the prices of basic foodstuffs that were the main commodities prior to the Industrial Revolution. The challenge is to find a way to quantify the efficiency of such techniques in different societies in different time periods in a comparable manner.

As pointed out, more efficient risk management techniques should lead to less variance in prices. Hence, measures of dispersion of prices are often used to capture market efficiency. The problem with the CV and related measures, however, is that they include more than just the effects of the risk reducing techniques listed above. They also include a volatility component that arises from inflation and different agricultural and demand structures. Although they clearly influence volatility, these factors have no direct relation with market efficiency. However, they affect the unconditional variance and, hence, need to be filtered out in order to compare market efficiency over time as well as across regions/countries.

These factors may influence the estimated market efficiency either directly or via the trend. In the next section, we will show that if there is a trend in the series, or if the price series has unit root (not unexpected in case of prices), the longer the chosen period, the more the calculated dispersion is going to grow. As such, without first detrending the series, this exercise is faulty. Yet, even if we remove the trend, the variance of the series will have components that are region- and period specific, making it very difficult, if not impossible, to compare dispersion measures across different regions, which is discussed in Sect. 4.

3 The effect of trend on the variance of time series

As discussed above, the timing of CV estimates may seriously distort the picture in the face of trends in the series such as those caused by, for example, inflation. In the following, we examine two possibilities: a stationary time series with linear trend (deterministic trend model) and a unit root process with or without trend (that is, with or without a drift parameter).

Let us assume that our series is stationary and can be modeled as follows:

$$y_t = \beta_0 + \beta_1 X_t + \gamma t + u_t \tag{1}$$

where $t = 1, 2, \ldots, T$ and $u_t \sim \mathrm{IID}(0, \sigma_u)$ and X is some exogenous variable ($\mathrm{Cov}(X,u) = 0$).

The variance of y around its arithmetical mean (unconditional variance) is:

$$\mathrm{Var}(y) = \beta_1^2 \mathrm{Var}(X) + \gamma^2 \mathrm{Var}(t) + 2\beta_1\gamma \mathrm{Cov}(X, t) + \mathrm{Var}(u) \tag{2}$$

For simplicity, let us assume that the variable X has no trend, so $\mathrm{Cov}(X,t) = 0$. In that case, the variance of y will depend on time in a monotonous way through the variance of the time trend. The variance of the trend can be expressed as follows (Hamilton 1994, p. 456):

$$\mathrm{Var}(t) = \frac{1}{T}\sum_{t=1}^{T} t^2 - \frac{1}{T^2}\left(\sum_{t=1}^{T} t\right)^2 \text{ where } \sum_{t=1}^{T} t^2 = T(T+1)(2T+1)/6 \text{ and } \times \sum_{t=1}^{T} t = T(T+1)/2 \tag{3}$$

which results in the following: $\mathrm{Var}(t) = \frac{1}{12}(T^2 - 1)$. Clearly, if we choose a longer period to estimate the variance of our series (T grows), it will inflate the variance of y. Note that this effect is independent of the sign of the time trend.

Yet, the example above focuses solely on a deterministic trend model. Let us now take a more likely case when our series is not stationary. This is expected in the case of a price series, especially when the conditions of a weak form of efficient markets are fulfilled. This means that no one can "outsmart" the market to make profit using public (or past) information. In a well-functioning market, agents will immediately use the information, if it is available, and eliminate the extraordinary profit. In short, price changes are not predictable from past information and our best guess for the next period price is the current one. Such a series is called a random walk (with no trend) or a random walk with drift (if there is a trend) and is found even in ancient economies such as Babylon ca. 200BC (Temin 2002).

Let us start with the following equation:

$$y_t = \gamma + y_{t-1} + u_t \tag{4}$$

where γ is the drift parameter ($\gamma = 0$ means no trend) and $u_t \sim \mathrm{IID}(0, \sigma_u)$. By repeated substitution, we arrive at the following expression: $y_T = \gamma T + \sum_{t=1}^{T} u_t$. Since the effect of past innovations will not wear off in this model, their effect on the variance will accumulate: $\mathrm{Var}(y_T) = \sum_{t=1}^{T} \mathrm{Var}(u_t) = T \cdot \mathrm{Var}(u)$. Again, we find that with the presence of unit root, the longer the period we use to calculate the variance and the derived dispersion measures, the more "volatility" we will find. As such, these measures are seriously misleading. For example, the sixteenth century witnessed massive inflation (Munro 2003). As can be seen in Table 1, this means that the CV is inflated by the underlying trend in price level. However, this is by no means an indication of deteriorating conditions or market disintegration in this period.[4] As we show in the following section, simple detrending techniques, such as using a deterministic trend or using the CV of the first difference of prices, are not necessarily ideal solutions either.[5]

4 The effect of structural differences on the variance of price series

The trend clearly has an important effect on volatility measures arising from inflation, technology, etc. Yet, even if one removes the trend from the series, the lack of comparability still remains an issue. In order to see the reason for this, one needs to think in terms of a structural model of prices, which ultimately is determined both by those factors reducing risk (as outlined in Sect. 2) and by those factors that are instrumental to the economies but not intended to reduce risk such as inflation and the agricultural and demand structures (see Sect. 1). Here, the last variables, of course, can be predicted (and, hence, captured by a structural model), while the first one manifests itself by the reduced effect of external shocks.

Let us assume that the price and quantity of commodity i is determined by the following system of supply and demand equations:

[4] This applies to both the cross-sectional variance and the CV that are frequently used to draw conclusions about spatial market integration. If the regional prices are non-stationary (contain unit root) and not cointegrated, it is highly probable that they will diverge. As such, the cross-country variance should also increase over time. If the series have different trends, the problem is even more aggravated. Since empirical studies rather search for a reduction in interregional variance, this observation has no serious consequence on the existing literature. When we find a reduction in the cross-regional or cross-country prices, there is no reason to believe that it is not what it seems.

[5] Let us assume that the series is close to having a unit root but fulfills the stationary requirements, for example, $y_t = \lambda_0 + \lambda_1 y_{t-1} + \lambda_2 x_t + e_t, 0 < |\lambda_1| < 1$. First differencing will neither remove the effect of the previous period prices nor that of the exogenous variables: $\Delta y_t = (\lambda_1 - 1)y_{t-1} + \lambda_2 x_t + e_t$. That is, simply taking either the CV or the variance of a first-differenced price series may still contain a lot of different factors besides the residual variance, and the problem outlined in Sect. 4 is still valid. The problem can be solved through first differencing only if one is sure (by means of testing) that the data-generating process is like in (4).

$$q_{i,t}^{S} = \alpha E_{t-1}p_{i,t} + \sum_{j=1}^{k} \beta_j X_{j,t} + u_t \text{ supply, } u_t \sim \text{IID}(0, \sigma_u) \tag{5}$$

$$q_{i,t}^{d} = \gamma p_{i,t} + \sum_{m=1}^{r} \delta Z_{m,t} + v_t \text{ demand, } v_t \sim \text{IID}(0, \sigma_v) \tag{6}$$

where q^{S} and q^{d} denote the quantity supplied and demanded, p_t and $E_{t-1}p_t$ are the current and the expected price of product i, and X and Z are other factors that affect supply and demand, respectively. X may contain different exogenous factors such as wars, weather conditions, and past prices of substitutes; Z denotes variables such as the price of other products that are either substitutes or complements of commodity i, or exogenous factors affecting demand, such as income or different political variables.

Hence, in equilibrium $q^{\mathrm{S}} = q^{\mathrm{d}}$, we can express the reduced form for the price of commodity i as follows:

$$\begin{aligned} p_{i,t} &= \frac{\alpha}{\gamma} E_{t-1}p_{i,t} + \sum_{j=1}^{k} \frac{\beta_j}{\gamma} X_{j,t} - \sum_{m=1}^{r} \frac{\delta_m}{\gamma} Z_{m,t} + \frac{u_t - v_t}{\gamma} \\ &= \frac{\alpha}{\gamma} E_{t-1}p_{i,t} + \sum_{j=1}^{k} \Pi_j X_{j,t} - \sum_{m=1}^{r} \Theta_m Z_{m,t} + e_t, \\ & e_t \sim \text{IID}(0, \sigma_e) \end{aligned} \tag{7}$$

We assume that the variables X and Z are indeed exogenous (or at least predetermined), $\text{Cov}(X,e) = \text{Cov}(Z,e) = 0$ and, furthermore, that the expectations for the current price are uncorrelated with X, Z and e.[6] The unconditional variance of p_i is as follows:

$$\begin{aligned} \text{Var}(p_{i,t}) = & \left(\frac{\alpha}{\gamma}\right)^2 E_{t-1}p_{i,t} + \sum_{j=1}^{k} \Pi_j^2 \text{Var}(X_j) + \sum_{m=1}^{r} \Theta_m^2 \text{Var}(Z_m) + \sum_{j<l} 2\Pi_j \Pi_l \text{Cov}(X_j, X_l) \\ & + \sum_{m<n} 2\Theta_j \Theta_n Cov(Z_m, Z_n) + \sum_{j=1}^{k} \sum_{j<m}^{r} 2\Pi_j \Theta_m \text{Cov}(X_j, Z_m) + \text{Var}(e_t) \end{aligned} \tag{8}$$

That is, the variance of commodity prices and all derived measures, such as the coefficient of variation, will contain not only the effect of shocks on prices (Var(e)) but also that of the price volatility of related products, exogenous factors and their relations measured by the covariances. The latter factors are important, since they reflect region-specific conditions and differences in main crops (relationship between weather conditions and the yield of different crops), tastes (relationship among the prices of different products), and the diversification of the consumption structure (the numbers and signs of price covariances that enter the equation). If, for example, we have a society where 80% of the income is spent on two main products

[6] The expectations are formed in period $t-1$ without any knowledge of the value of X or Z in t.

with different environmental requirements/sensitivity, we can expect that in that particular region, the price covariance between the two will be lower than in a country where the two main products are similar (see wheat–rice in the North of China vs. wheat–barley in Europe), or where people are dependent on a single main foodstuff.

Undeniably, the variance of prices contains essentially all the information we need to judge the efficiency of markets, but it also contains a lot of region/period-specific factors that are not possible to separate. So, if one compares the CV of different regions, even if the problems of trend and non-stationarity have been taken care of, it is still not possible to ascertain exactly what is being measured. One could of course estimate a structural equation (at least the reduced form price equation) and use the coefficients to have some estimates of the effect of different factors, but in most cases, we do not have such a detailed set of exogenous variables available for historical analysis. For this reason, we suggest not using CV and related measures on time series to draw conclusions about market efficiency or market integration in a particular region or country over time.

5 Alternative methodology: conditional heteroscedasticity

Our suggestion to get around the problem is to apply a technique widely used in financial econometrics and macroeconometrics, a conditional heteroscedasticity model based on the standard autoregressive models that are occasionally used in market efficiency studies (i.e., Söderberg 2004). As we saw above, the unconditional variance of price series consists of two parts: the variance of the residual term and the variance of the conditional mean (fitted value) around the arithmetical average. Although the latter has a lot of information, the lack of data will prevent us from separating what we need from the region/period-specific factors within a structural model. With conditional heteroscedasticity methods, we concentrate on the variance around the conditional mean, that is the residual variance only.

The residual variance will reflect the share of shocks in total variance, that is the effect of unexpected events on price volatility. If markets are more integrated, or if the institutional background is more efficient, these unexpected events should have a reduced effect on prices. The error is, of course, a random variable, so its magnitude may change. For our purposes, the residual can be modeled as follows:

$$e_t = \chi(\Omega_t) \cdot \varepsilon_t \tag{9}$$

where

$$\varepsilon_t \sim \mathrm{IID}(0, \sigma_\varepsilon) \tag{10}$$

where ε is a random variable representing the size of the shocks, and χ is a multiplier showing us the effect of the shock on prices. The factor χ may obviously depend on the degree of market integration or other factors (denoted by Ω_t), and in case of a tendency of improvement or deterioration, it should be dependent on time. We can assume that the size of shocks is, on average, zero and homoscedastic. In other words, the magnitude of the shocks does not depend on time or the order of the observations. Of course, there may be periods when shocks are larger and more common (wars, disasters, sudden changes in climate) but, if we take a reasonably long sample, this condition should hold. This also means that in order to have meaningful results on the markets' ability to efficiently cope with risks, short periods should not be analyzed. If we assume that the magnitude of the shocks and the parameter χ are independent, we obtain for the residual variance:

$$\mathrm{Var}(e) = \mathrm{Var}(\chi_t) \cdot \mathrm{Var}(\varepsilon_t) + \bar{\chi}\mathrm{Var}(\varepsilon_t) = (\mathrm{Var}(\chi_t) + \bar{\chi}) \cdot \sigma_\varepsilon^2 \tag{11}$$

If we find a trend-like behavior in the residual variance (or any similar measures, such as the standard deviation or the mean absolute deviation of the residual), we can interpret it as a sign of the market's ability to cope with the effect of shocks. The cornerstone of the suggested method is our assumption regarding the random shocks. While our assumption about the homoscedasticity of ε within the same country or region sounds feasible, it is less likely that the shocks have the same variance across all regions as well, making this method not ideal for cross-country comparisons. Even acknowledging this weakness, the residual variance still contains fewer incomparable factors than CV. A possible solution might be to apply a model that allows country-specific differences in the error term by combining, for example, the conditional heteroscedasticity model with a panel analysis. In this paper, we do not apply such a method. However, using a panel can be advantageous when one has enough observations to make a panel dataset, and it is reasonable to assume that the underlying data-generating process is similar in all series.

There are several different approaches to model conditional heteroscedasticity. The early methodology proposed by Engle (1982) suggests that the estimation be carried out in two steps. In the first step, one models the conditional mean of the time series (mean equation) as an AR(p) model (or a structural model) so that there remains no serial correlation in the residuals (there is a heteroscedasticity, of course, so robust standard errors are required for model selection), and those that are squared are modeled in the second step as an AR process (variance equation). This leads to the well-known ARCH specification:

$$y_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i y_{t-i} + u_t \tag{12}$$

and

$$\hat{u}_t^2 = \phi_0 + \sum_{j=1}^{q} \phi_j \hat{u}_{t-q}^2 + \sum_{l=1}^{r} \Omega_{l,t} \tag{13}$$

where Ω denotes the effect of r exogenous factors that may explain the heteroscedastic nature of the residual.

Bollerslev (1986) suggested the generalized autoregressive heteroscedasticity (GARCH), which may circumvent the problems with the ARCH specification and lead to more efficient estimates.

$$\sigma_{u,t}^2 = \phi_0 + \sum_{k=1}^{n} \eta_k \sigma_{u,t-k}^2 + \sum_{j=1}^{q} \phi_j \hat{u}_{t-q}^2 + \sum_{l=1}^{r} \Omega_{l,t} \tag{14}$$

Obviously, this specification cannot be estimated with OLS. The two equations need to be estimated simultaneously using a maximum likelihood estimator. Unfortunately, since we often have gaps in the data and the ARCH/GARCH procedures in most econometric packages cannot handle this missing information, the second approach may be unsuitable for historical analysis. In those cases, it might be more useful to return to the two-step method using ARCH specification. Since in this paper we are looking for the reduction of some long-run tendencies of the residual variance, we use a time trend in the second step. If there are no gaps in the series, it is preferable to use the ML estimator. In practice, other ARCH/GARCH specifications might also be explored, such as the TARCH specification that allows for different effects of shocks with different signs, or the GARCH-M specification (Glosten et al. 1993) that allows for an effect of volatility on price level. In this paper, however, in order to make all estimations comparable, we use an ARCH(1) specification uniformly.

6 Empirical application

In this section, we illustrate the above method by applying a conditional heteroscedasticity model to four historical price series: two monthly (wheat prices in Pisa 1549–1716 [Malanima 1976] and Paris 1548–1698 [Baulant and Meuvret 1962; Poynder 1999]) and two annual series (rice prices in Hiroshima, Japan, 1620–1857 [Iwahashi 1981] and wheat prices in Vienna 1439–1800 [Pribram 1938]). Since the volatility measures are not comparable if the series have different frequencies, the monthly series are transformed to annual ones. Since it is possible that using annual series would distort our results, the same exercise is done with the monthly series as well. We find that the underlying trend in the residual variance does not change with the use of different frequency data. The Vienna series and the two monthly series have gaps in the data. In cases of the Vienna series and the Paris prices, there were so many gaps present that we needed to use the two-step procedure suggested by Engle (1982). The monthly wheat price from Pisa has a single gap in 1631, making it possible to estimate the ARCH model on each half of the series separately using an ML estimator. In order to make the results from the different series comparable, as noted in the previous section, we use the ARCH(1) specification for all series. We would like to stress that this decision reflects only our preference for comparability; however, in actual empirical usage, models should be selected for their fit or because of theoretical considerations. Using a more complex structure to model residual variance improved the efficiency of the estimation (lower standard errors) when we experimented with other specifications, but it did not fundamentally change the results.

We begin by reporting the annualized prices in the graphs below. All series exhibit large price increases in the sixteenth century, which is consistent with the influx of silver from the Americas and a strong increase in the minting of silver coins in Japan (Miyamoto 1999a, b, p. 59). Besides this common rise in prices, it is also clear that inter-annual volatility in all four series is exceptionally different (Figs. 1, 2, 3, 4).

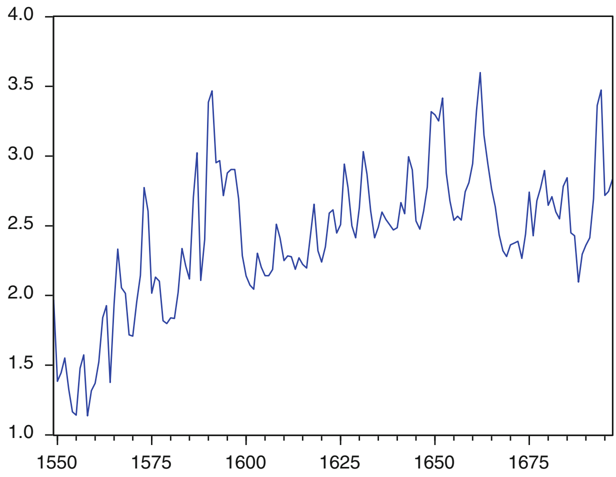

Fig. 1 Log of annual wheat prices in Paris, 1548–1698

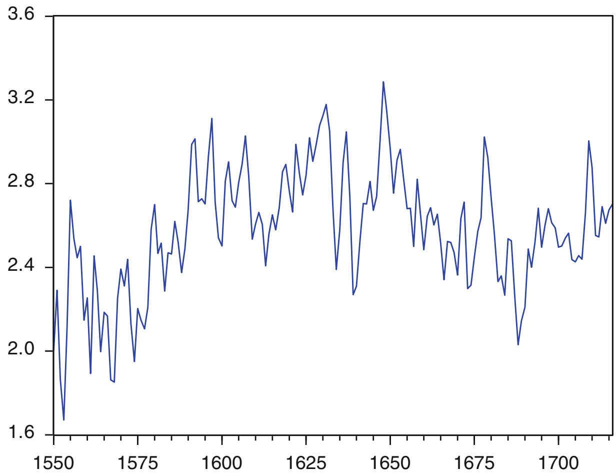

Fig. 2 Log of annual wheat prices in Pisa, 1549–1716

We start by estimating the standard measures of dispersion for the annual series (Table 2). Using the traditional measure to judge the degree of market integration/risk management, one would find that the wheat market of Pisa was especially efficient resulting in minimal volatility of prices, while Paris and Hiroshima seem to have roughly equal volatility, and Vienna had the highest degree of volatility.

Indeed, although volatility in both Paris and Hiroshima was of similar magnitude, the underlying reason is likely different. It has often been argued that in Paris, in the period being analyzed, markets were extremely volatile. Food shortages, over-emphasizing arable agriculture at the cost of pasture, and inflation all contributed to increasing price volatility. During the period from 1550 to 1600, the real price of

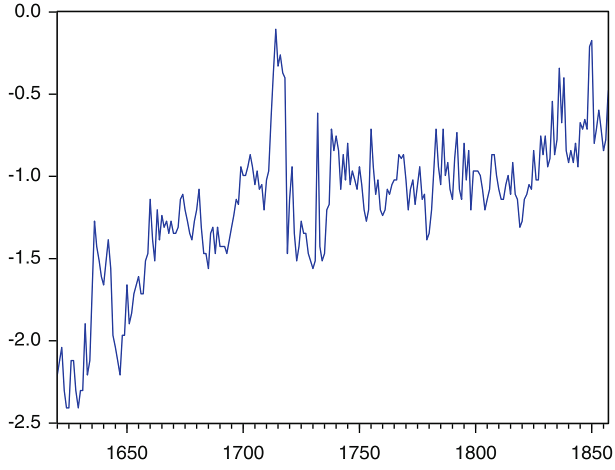

Fig. 3 Log of annual rice prices in Hiroshima, 1620–1857

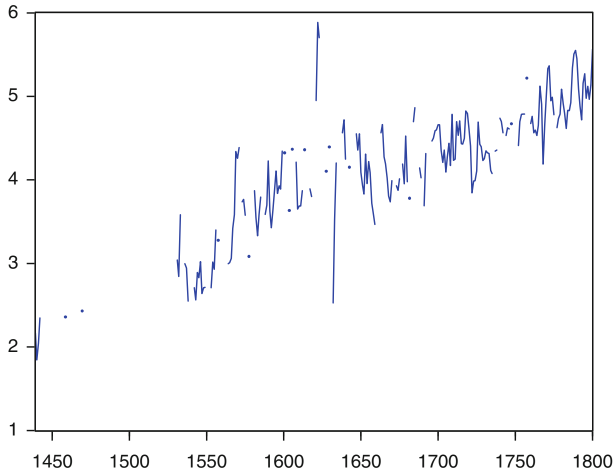

Fig. 4 Log of annual wheat prices in Vienna 1439–1800

wheat even trebled (Knecht 2001, p. 260). Conversely, in the seventeenth century in Japan, the growing population prompted the shogunate to enact demand suppressing policies, such as placing a limit on sake brewing, in order to keep rice prices down (Miyamoto 1999a, p. 57).These pressures eased in the late seventeenth century due to greater agricultural production. Hence, except for the Tenmei crop failures (1781–1789), prices remained relatively stable.

Viennese price fluctuations, however, were much higher. Although Vienna had relatively few problems with a supply side crisis because of its status as a main city in the Habsburg Empire (Weigl 2000, pp 162–163), it experienced extreme population

Table 2 Coefficient of variation and the standard deviation of the log prices

	Paris wheat prices		Hiroshima rice prices, annual 1620–1857	Pisa white wheat prices		Vienna wheat prices, annual, 1439–1800 (with gaps)
	Annual 1549–1697	Monthly Sept 1549–Aug 1698		Annual 1550–1817	Monthly Oct 1548–Jul 1818	
CV	0.497	0.543	0.409	0.392	0.412	0.683
Std dev of the log series	0.503	0.522	0.435	0.350	0.373	0.753

growth in combination with the fact that wheat was its most important staple (Sandgruber 1982, p. 141). These factors not only caused an increase in supply distribution to the poor (Weigl 2000, pp 198–199; Weigl 2001, p. 51), they also made the market more susceptible to supply side shocks. The most important of these shocks were the Turkish wars. In 1683, a Turkish army even laid siege to Vienna, which can clearly be seen in the variance of the price series. Finally, the Pisa series reflects the lowest volatility. This is caused in part by the minimal change in population and agricultural structure, and in part by the relative constancy of consumption. Persson (1999, p. 142) argues that the Tuscans had well-integrated trade networks and were more inclined toward reform. This led him to conclude that "the residual standard error for […] Pisa in the seventeenth century was at a level which seems to be a sort of *ancien régime* minimum, and that only in the era of the nineteenth-century transport revolution are lower residuals attained elsewhere" (Persson 1999, p. 111).

Hence, we find that exogenous factors like inflation, agricultural structure, and demand played a role in price volatility in all countries, but these are not necessarily directly related to risk management techniques. In Paris and Japan, after correcting for the effect of conditional variance, we find residual variances of similar magnitude. Both were subject to inflation and government intervention driving demand patterns but, in essence, no serious disturbances took place. In Vienna, however, the main source of inflation, external shocks and government policy, had a profound impact on volatility.

The first step of estimating a conditional heteroscedasticity model is to establish whether or not the log of the price series is stationary. In Table 3, we report the results from three unit root tests, all of them designed to improve the low power of the traditional Dickey–Fuller-type unit root tests when rejecting the null hypothesis of non-stationarity. In most cases, the test statistics are consistent with each other, implying that the price series are stationary. This is the only case when there is contradiction between the test results and the annual log prices of wheat in Pisa. The Philips–Perron test rejects the null hypothesis of non-stationarity at 10%, while the DF–GLS test suggests that the series are not stationary. The Ng–Perron test is, again, contradictory. In order to assure comparability of our results, we take the first difference of all series.

For the annual series for Paris, Pisa, and Hiroshima, we could use the standard ML procedure to estimate the mean and the variance equations simultaneously. In

Table 3 Unit root tests (with linear trend)

	Philips–Perron	DF–GLS	Ng–Perron test
Paris log of wheat prices 1549–1697 (annual)	−4.388 ($p < 0.01$)	−3.389 ($p < 0.05$)	MZa = −20.23 ($p < 0.05$)
			MZt = −3.179 ($p < 0.05$)
			MSB = 0.157 ($p < 0.01$)
			MPT = 4.514 ($p < 0.01$)
Paris log of wheat prices 1549M09–1698M09 (monthly)	−6.552 ($p < 0.01$)	−3.710 ($p < 0.01$)	MZa = −27.22 ($p < 0.01$)
			MZt = −3.67 ($p < 0.01$)
			MSB = 0.135 ($p > 0.01$)
			MPT = 3.45 ($p > 0.01$)
Pisa log of wheat prices 1550–1817 (annual)	−4.856 ($p < 0.01$)	−2.578 ($p > 0.1$)	MZa = −16.78 ($p < 0.1$)
			MZt = −2.889 ($p < 0.1$)
			MSB = 0.172 ($p < 0.05$)
			MPT = 5.479 (p < 0.1)
Pisa log of wheat prices (monthly), 1548M10–1631M07	−6.240 ($p < 0.01$)	−6.141 ($p < 0.01$)	MZa = −74.14 ($p < 0.01$)
			MZt = −6.07 ($p < 0.01$)
			MSB = 0.082 ($p > 0.01$)
			MPT = 1.308 ($p > 0.01$)
Pisa log of wheat prices (monthly), 1631M10–1818M07	−3.539 ($p < 0.01$)	−3.471 ($p < 0.05$)	MZa = −27.58 ($p < 0.01$)
			MZt = −3.70 ($p < 0.01$)
			MSB = 0.134 ($p > 0.01$)
			MPT = 3.383 ($p > 0.01$)
Hiroshima log of rice prices 1620–1857	−5.423 ($p < 0.01$)	−3.626 ($p < 0.01$)	MZa = −24.65 ($p < 0.01$)
			MZt = −3.510 ($p < 0.01$)
			MSB = 0.142 ($p > 0.01$)
			MPT = 3.697 ($p > 0.01$)
Vienna log of wheat prices 1439–1800	−4.593 ($p < 0.01$)	−3.928 ($p < 0.01$)	MZa = −31.38 ($p < 0.01$)
			MZt = −3.956 ($p < 0.01$)
			MSB = 0.126 ($p > 0.01$)
			MPT = 2.931 ($p > 0.01$)

case of the Vienna series, the gaps do not allow us to use this procedure, so we estimate the expected value of the first difference of the log wheat prices, and then we model the square of the residuals in a second step.

With the exception of the Hiroshima series, we cannot reject the normality of the residuals at 1%; however, with such a large number of observations, even non-normality should not pose a problem (Central Limit Theorem). Additionally, the residuals do not have any significant autocorrelation. The linear trend yields a significant coefficient in the second step only in case of the Pisa series.

In Figs. 5, 6, 7, and 8, we plot the conditional standard deviation of the annual price series for the four cities. In Paris, Pisa, and Vienna, we find a clear downward trend (even though the trend coefficient is statistically significant only

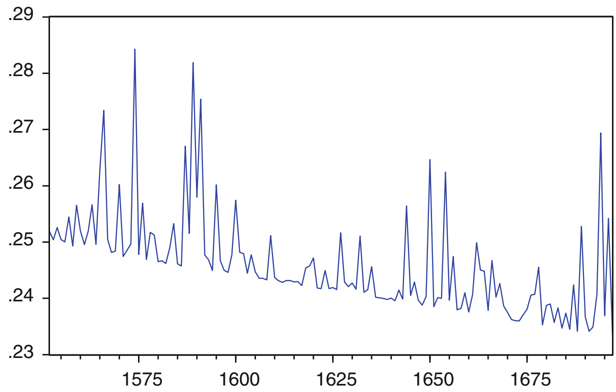

Fig. 5 Conditional standard deviation of the residuals, wheat prices in Paris 1549–1697

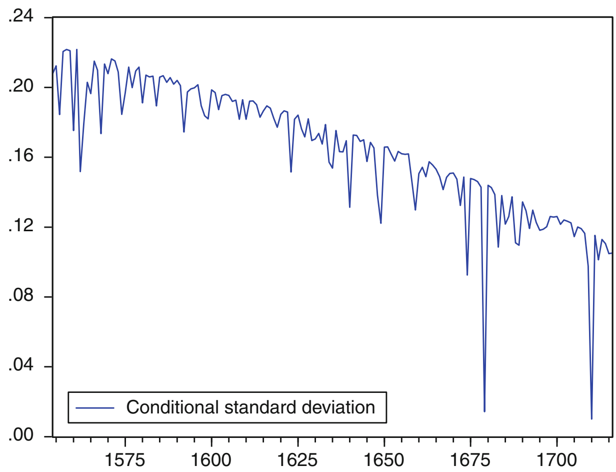

Fig. 6 Conditional standard deviation of the residuals, wheat prices in Pisa 1550–1716

in case of Pisa). Although the standard deviations start out at different levels (the highest in Vienna around 0.35 and the lowest in Hiroshima and Pisa with around 0.2), the reduction is quite conspicuous. In the case of Pisa, the standard deviation is halved, while in Paris and Vienna, it is reduced by roughly 5 and 32%, respectively. Hiroshima seems to be the exception where even the graphs do not show any sign of a decreasing conditional volatility. This is not surprising, however, given that the early volatility, as discussed before, was caused by the demand structure and inflation, which were both factors that need to be removed as they have no direct relation with the risk factors in markets (Miyamoto 1999b, p. 120).

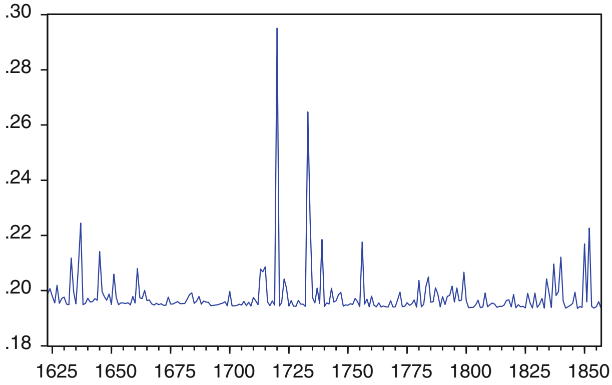

Fig. 7 Conditional standard deviation of the residuals, rice prices in Hiroshima 1620–1857

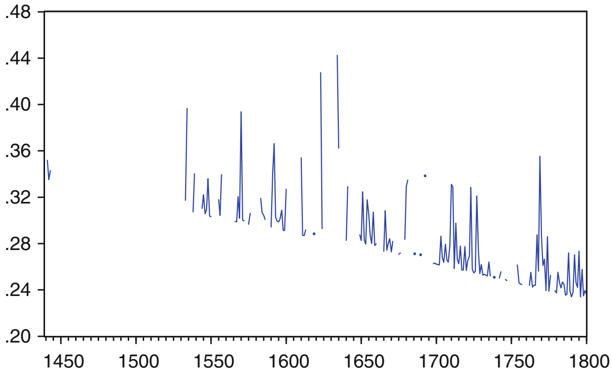

Fig. 8 Conditional standard deviation of the residual, Vienna wheat prices 1439–1800

So far, we discussed the annual series. As a second step, we use the monthly price series to see if using different frequency data alters the results. As we noted at the beginning of this section, the Pisa series has just a single gap, making it possible to use the ML estimator at the cost of cutting the sample in two. In case of the Paris prices, however, we had three gaps lasting for only a few months but estimating an ARCH model on four different, shorter periods. This is in contradiction with our own suggestions in Sect. 5 on the length of the sample period. If shorter periods were used, there would be far too great a risk that the observed variance is not an actual trend but rather the effect of some temporary fluctuations. The regression results are reported in Tables 4 and 5.

Even though some of the statistics change with the different frequencies of data used, the picture has largely remained the same. We find a significant negative trend in the residual variance (or standard deviation) in two of the series. The degree of improvement is slight in Paris, while in Pisa, it is significant in the

Table 4 Conditional heteroscedasticity estimates of annual differenced series

	Paris 1549–1697	Pisa 1550–1817	Hiroshima 1620–1857	Vienna 1439–1800
Mean equation				
Constant	0.018 (1.93)	0.006 (1.12)	0.007 (0.75)	0.026 (1.16)
AR(1)	–	0.057 (0.86)	−0.266 (−3.74)	–
AR(2)	−0.372 (−3.74)	−0.403 (−6.63)	−0.152 (−2.28)	–
AR(3)	–	−0.184 (−2.80)	–	–
AR(4)	–	−0.111 (−1.96)	–	–
Variance equation				
Constant	0.062 (3.29)	0.032 (6.20)	0.038 (2.99)	0.124 (3.59)
ARCH(1)	0.039 (0.56)	0.095 (1.30)	0.041 (0.46)	0.124 (1.81)
Trend	−0.0000544 (−0.25)	−0.0000742 (−3.04)	−0.00000239 (−0.037)	−0.000177 (−1.34)
Diagnostic tests				
R^2	0.148	0.189	0.082	0 (only constant)
	5.388 ($p = 0.250$)	0.840 ($p = 0.359$)	3.068 ($p = 0.382$)	3.495 ($p = 0.347$)
Q(12)	6.462 ($p = 0.640$)	14.359 ($p = 0.073$)	8.223 ($p = 0.607$)	5.602 ($p = 0.827$)
Jarque–Bera test of the normality of the residual	3.249 ($p = 0.197$)	1.027 ($p = 0.598$)	302.5 ($p = 0.000$)	9.177 ($p = 0.011$)
Std. error of the regression	0.268	0.159	0.200	0.295

z-statistics are reported in parentheses, with the exception serial correlation and normality tests, where *p* values are reported

Table 5 Conditional heteroscedasticity estimates of differenced monthly series

	Paris log of wheat price[a]	Pisa log of wheat price	
	1549M09–1698M08	1548M12–1631M07	1631M12–1818M07
Constant	0.007 (11.96)	0.002 (0.44)	0.006 (2.40)
AR(1)	0.0097 (1.27)	0.154 (3.89)	0.066 (2.58)
AR(2)	–	−0.078 (−2.60)	–
AR(11)	–	–	−0.078 (−2.79)
AR(12)	–	−0.191 (−5.08)	–
Trend	−0.00000107 (−2.22)	–	–
Constant	0.074 (13.68)	0.0102 (8.38)	0.0029 (3.76)
ARCH(1)	0.234 (4.90)	0.215 (3.18)	0.287 (6.52)
Trend	−0.00000958 (−1.96)	−0.00000961 (−6.98)	−0.000000154 (−0.45)
R^2	0.005	0.182	0.186
Q(5)	19.01 ($p = 0.001$)	6.569 ($p = 0.037$)	5.469 ($p = 0.141$)
Q(12)	61.21 ($p = 0.001$)	14.811 ($p = 0.096$)	13.651 ($p = 0.189$)
Jarque–Bera test of the normality of the residual	8,700 ($p < 0.01$)	248.6 ($p < 0.01$)	1,878 ($p < 0.01$)
Std. error of the regression	0.102	0.085	0.059

Seasonal dummies are included but not reported in the mean equation

[a] Due to outliers, the dependent variable in the second stage (variance equation) is the absolute value of the residual from the first step (mean equation)

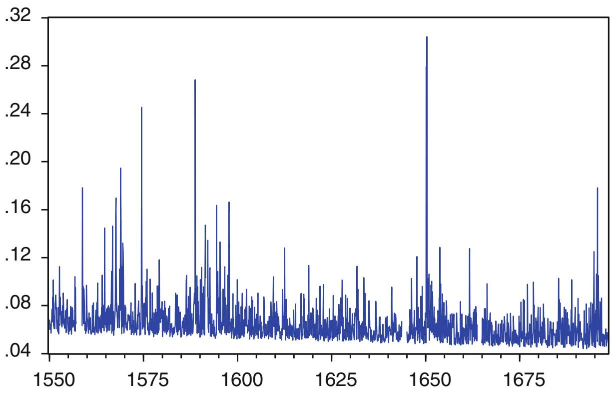

Fig. 9 Conditional standard deviation of the residuals, wheat prices in Paris 1548M09–1698M08

sixteenth century and the first decades of the seventeenth century, followed by insignificant improvement throughout the rest of the sample period (Figs. 9, 10a, b). Therefore, using annual data does not seem to be entirely misleading. Nevertheless, monthly series should be preferred for market efficiency analysis wherever possible.

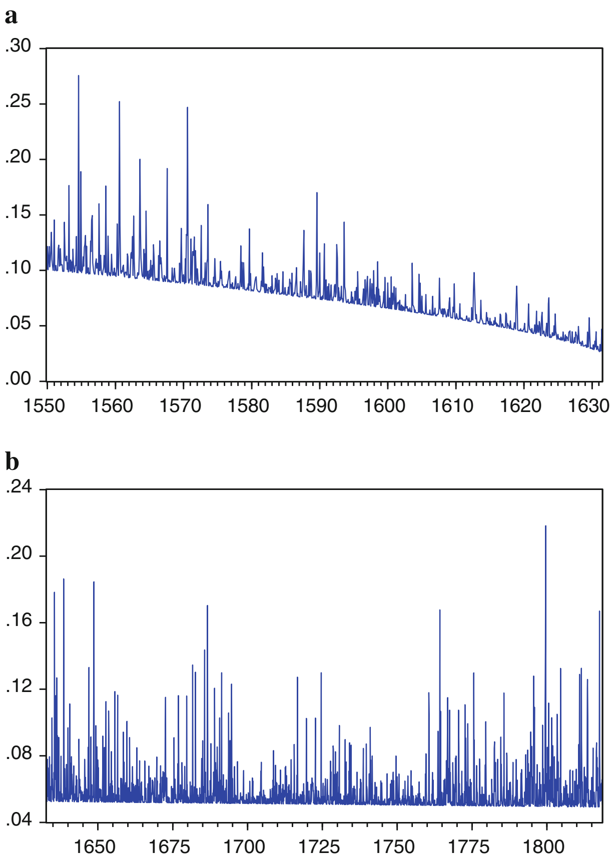

Fig. 10 **a** Conditional standard deviation of the residuals, wheat prices in Pisa 1548M10–1631M07. **b** Conditional standard deviation of the residuals, wheat prices in Pisa 1631M09–1818M07

7 Conclusion

In this paper, we follow part of the literature that argues that using traditional dispersion measures, such as the coefficient of variation, as indicators for the degree of market integration is misleading because they include country- and time-specific factors that indirectly influence market efficiency. This has two empirical consequences. First, in both non-stationary as well as stationary price series, the variance is inflated by the trend. This leads to erroneous conclusions regarding the degree of market integration in the presence of inflation, such as the price revolution during the sixteenth century. Secondly, the variance of the log prices contains information on many factors that are either not related to market integration, but are rather region specific, or not comparable or separable. Hence, both the standard CV and the detrended version will bias the estimates of market efficiency. As an alternative, to test for any improvement over time, we suggest using the standard deviation of the residual (or the standard error of the regression) to compare the degree of market integration among different regions together with a conditional heteroscedasticity approach.

Applied to four heterogeneous price series (Pisa, Hiroshima, Paris, and Vienna), we find that in all cases, the CV indicates a higher level of volatility since it is a fundamental measure of unconditional volatility. Hence, using the CV, or related measure, on commodity price series is likely to lead to biased, noisy estimates of market efficiency. Unfortunately, the amount of overestimation depends on the presence of factors such as inflation and the demand and agricultural structures, which, although they influence price volatility, are not directly related to market efficiency. Applying a conditional heteroscedasticity model, we find that in Pisa, Vienna, and Paris, the price volatility declined (and market efficiency increased) in the early modern period, which compares well with the established view of increasing market efficiency from ca. 1600 forward (Persson 1999; Jacks 2004).

References

Andreau J (2002) Twenty years after Moses I. Finley's The Ancient Economy. In: Scheidel W, Von Reden S (eds) The ancient economy. Edinburgh University Press, Edinburgh, pp 33–49

Basini GL (1974) Sul Mercato di Modena Tra Cinque e Seicento: Prezzi e Salari. Dott. A Giuffré, Milano (downloaded from http://www.iisg.nl/hpw/data.php#italy)

Bateman V (2007) The evolution of markets in early modern Europe, 1350–1800: a study of grain prices. University of Oxford, Department of Economics discussion paper series No. 350

Baulant M, Meuvret J (1962) Prix des cereales extraits de la mercuriale de Paris (1520-1688): 2 vols. (Paris, 1962). (Vol I and II, p. 4-45 and 45-81). (Data downloaded from http://www.iisg.nl/hpw/data.php#france)

Bollerslev T (1986) Generalized autoregressive conditional heteroskedasticity. J économ 31(3):307–327

Britnell RH, Campbell BMS (eds) (1995) A commercialising economy: England, 1086 to c1300, 1st edn edn. Manchester University Press, Manchester

Clark G (2004) The price history of english agriculture, 1209-1914. Res in Econ Hist 22: 41-124. (downloaded from http://www.iisg.nl/hpw/data.php#united)

De La Roncière C (1982) Prix et Salaires à Florence au XIVe Siècle, 1280–1380. Palais Farnèse: Ecole Française de Rome. (downloaded from http://www.iisg.nl/hpw/data.php#italy)

Engle RF (1982) Autoregressive conditional heteroscedasticity with estimates of variance of United Kingdom inflation. Econometrica 50(4):987–1007

Federico G, Persson KG (2007) Market integration and convergence in the world wheat market, 1800–2000. In: Hatton TJ, O'Rourke KH, Taylor AM (eds) The new comparative economic history. Essays in Honor of Jeffrey G. Williamson. MIT Press, Cambridge, pp 87–114

Fenoaltea S (1976) Risk, transaction cost, and the organization of medieval agriculture. Exp Econ Hist 13(2):129–151

Glosten LR, Jagannathan R, Runkle DE (1993) On the relation between the expected value and the volatility of the nominal excess return on stocks. J Finance 48(5):1779–1801

Hamilton JD (1994) Time-series analysis. Princeton University Press, Princeton

Iwahashi M (1981) Kinsei Nippon Bukka-shi no Kenkyu, Tokyo Ohara Shinseisha. (Data downloaded from http://www.iisg.nl/hpw/data.php#japan)

Jacks D (2004) Market integration in the North and Baltic Seas, 1500–1800. J Eur Econ Hist 33(3):285–329

Jacks D (2005) Intra- and international commodity market integration in the Atlantic economy. Explor Econ Hist 42(3):381–413

Keller W, Shiue CH (2007) Market integration and economic development: a long-run comparison. Rev of Dev Econ 11(1):107–123

Knecht RJ (2001) The Rise and Fall of Renaissance France: 1483–1610, 2nd edn. Wiley-Blackwell, Oxford

Komlos J, Landes R (1991) Anachronistic economics: grain storage in medieval england. Econ Hist Rev 44(1):36–45

Malanima P (1976) Aspetti di mercato e prezzi del grano e della segale a Pisa dal 1548 al 1818. in *Ricerche di storia moderna*, I, Pisa, Pacini, 1976, pp 288-327. (Data downloaded from http://www.iisg.nl/hpw/data.php#italy)

McCloskey D, Nash J (1984) Corn at interest: the extent and cost of grain storage in medieval England. Am Econ Rev 74(1):174–187

Miyamoto M (1999a) Quantitative aspects of Tokugawa economy. In: Hayami A, Saito O, Toby RP (eds) Emergence of economic society in Japan 1600–1859. Oxford University Press, Oxford, pp 36–84

Miyamoto M (1999b) Prices and Macroeconomic Dynamincs. In: Hayami A, Saito O, Toby RP (eds) Emergence of economic society in Japan 1600–1859. Oxford University Press, Oxford, pp 119–158

Munro J (2003) The monetary origins of the 'Price Revolution': South-German Silver Mining, Merchant-Banking, and Venetian Commerce, 1470–1540. Department of Economics and Institute for Policy Analysis University of Toronto

Ó Gráda C (1992) Ireland's great famine. ReFRESH 15:15–18

Overton M (1996) Agricultural revolution in England: the transformation of the Agrarian economy 1500–1850. Cambridge University Press, Cambridge

Özmucur S, Pamuk S (2007) Did European commodity prices converge during 1500–1800? In: Hatton TJ, O'Rourke KH, Taylor AM (eds) The new comparative economic history. Essays in Honor of Jeffrey G. Williamson. MIT Press, Cambridge, pp 59–86

Persson KG (1999) Grain markets in Europe, 1500–1900: integration and deregulation. Cambridge University Press, Cambridge

Poynder N (1999) Grain storage in theory and history. Paper presented at the Third Conference of the European Historical Economics Society, Lisbon, October 29–30

Pribram AF (1938) Materialien zur Geschichte der Preise und Löhne in Österreich. Band I. Carl Ueberreuters, Vienna

Reis J (2005) Economic growth, human capital formation and consumption in Western Europe Before 1800. In: Allen RC, Bengtsson T, Dribe M (eds) Living standards in the past. New Perspectives on Well-Being in Asia and Europe. Oxford University Press, Oxford, pp 195–227

Sandgruber R (1982) Die Anfänge der Konsumgesellschaft: Konsumg¨uterverbrauch, Lebenstandard und Alltagskultur in Österreich im 18. und 19. Jahrhundert. Oldenburg, München

Slotsky AL (1997) The Bourse of Babylon. Market quotations in the astronomical diaries of Babylonia. CDL Press, Bethesda

Söderberg J (2004) Prices in the medieval Near East and Europe. Paper presented at the conference Towards a Global History of Prices and Wages, 19-21 Aug. 2004. (downloaded from http://www.iisg.nl/hpw/papers/soderberg.pdf)

Studer R (2008) India and the great divergence: assessing the efficiency of grain markets in eighteenth- and nineteenth-century India. J Econ Hist 68(2):393–437

Temin P (2002) Price behaviour in Ancient Babylon. Explor Econ Hist 39(1):46–60

Van der Eng P (1996) Agricultural growth in Indonesia: productivity change and policy impact since 1880. MacMillan Press Ltd, Basingstroke [etc.]

Vargyas P (2001) A history of Babylonian prices in the first millennium BC. 1. Prices of the basic commodities. Heidelberger Studien zum Alten Orient 10, Heidelberger Orientverlag, Heidelberg

Weigl A (2000) Demographischer Wandel und Modernisierung in Wien. Pichler Verlag, Wien

Weigl A (2001) Residenz, Bastion und Konsumptionsstadt: Stadtwachstum und demographische Entwicklung einer werdenden Metropole. In: Weigl A (ed) Wien im Dreißigjährigen Krieg. Bevölkerung—Gesellschaft–Kultur—Konfession. Böhlau, Wien, pp 31–105

Will P-E, Bin Wong R, Lee J (1991) Nourish the people: the state civilian granary system in China, 1650–1850. Center for Chinese Studies, The University of Michigan, Ann Arbor